

Evolution over time of heavy vehicle volume in toll roads: A dynamic panel data to identify key explanatory variables in Spain

Juan Gomez , José Manuel Vassallo

A B S T R A C T

Improving the knowledge of demand evolution over time is a key aspect in the evaluation of transport policies and in forecasting future investment needs. It becomes even more critical for the case of toll roads, which in recent decades has become an increasingly common device to fund road projects. However, literature regarding demand elasticity estimates in toll roads is sparse and leaves some important aspects to be analyzed in greater detail. In particular, previous research on traffic analysis does not often disaggregate heavy vehicle demand from the total volume, so that the specific behavioral patterns of this traffic segment are not taken into account. Furthermore, GDP is the main socioeconomic variable most commonly chosen to explain road freight traffic growth over time. This paper seeks to determine the variables that better explain the evolution of heavy vehicle demand in toll roads over time. To that end, we present a dynamic panel data methodology aimed at identifying the key socioeconomic variables that explain the behavior of road freight traffic throughout the years. The results show that, despite the usual practice, GDP may not constitute a suitable explanatory variable for heavy vehicle demand. Rather, considering only the GDP of those sectors with a high impact on transport demand, such as construction or industry, leads to more consistent results. The methodology is applied to Spanish toll roads for the 1990–2011 period. This is an interesting case in the international context, as road freight demand has experienced an even greater reduction in Spain than elsewhere, since the beginning of the economic crisis in 2008.

1. Introduction

Improving the knowledge of road demand evolution and estimating better traffic forecasts are critical aspects in properly evaluating transport policies and accurately forecasting future investment needs (Matas et al., 2012). Stakeholders involved in roads management (such as governments, and operators) find it indispensable to identify the key parameters influencing road demand, as well as to quantify the strength of the relationships between traffic and certain explanatory variables over time. This issue becomes even more critical in toll roads, as they are financed mainly through user's contributions. However, the state of knowledge concerning demand behavior for toll roads is still limited (Odeck and Brathen, 2008), and leaves some aspects to be investigated in greater detail.

Previous research studies generally pay little attention to road freight demand evolution over time. Methodological specifications on traffic analysis do not often disaggregate heavy vehicle demand from the total volume, so that the specific behavioral patterns of this segment of the traffic are not taken into account. Furthermore, the literature concerning road freight traffic is mainly focused on urban areas (Cherry and Adelakun, 2012; Holguín-Veras et al., 2006) or on quite specific tolled sections, such as bridges or tunnels (Hirschman et al., 1995; McKnight et al., 1992). By contrast, existing research explaining heavy vehicle demand evolution in interurban toll roads are sparse, and commonly include GDP as the only socio-economic explanatory variable in the analysis. Finally, the impact of the current economic crisis on road freight traffic has barely begun to be analyzed in the literature.

The aim of this paper is to contribute to a better knowledge of the evolution of heavy vehicle demand on interurban toll roads by identifying some of the key socioeconomic variables influencing traffic behavior. Through an original methodology, we discuss the suitability of GDP as a socioeconomic explanatory variable of road freight traffic on toll roads, and propose alternative variables. The main objective is thus to fill the research gap found in the literature regarding the socioeconomic variable that better explains the evolution of road freight demand over time. Additionally, this paper analyzes the effects of the economic crisis on heavy vehicle demand for toll roads, and tests the suitability of the explanatory variables chosen.

The methodology is applied to the Spanish toll road network, which represents a very interesting case in the international context. The deterioration of the economic environment in Spain since 2008 has had a great impact on the level of traffic in the tolled network, particularly as regards heavy vehicle demand. According to data from the Spanish Ministry of Transportation (Ministerio de Fomento, 2013), road traffic has undergone a reduction of 28% compared with the peak attained since 2007. Regarding heavy vehicle demand, traffic in toll roads has fallen, since the beginning of the crisis, after 6 years of consecutive decreases, by a full 40%. As a result, road freight demand has returned to levels of 1994, when the tolled network was 46% smaller. Revenues of private concessionaires have decreased by 10% in 2012 compared with levels in the previous year, which has led the government to take critical measures to relieve their financial situation. Then, we seek to evaluate to what extent significant reductions undergone by road freight traffic in recent years in Spain can be considered an anomalous fact when compared to previous trends.

This paper is organized as follows. After the introduction in Section 1, Section 2 summarizes the state of knowledge regarding heavy vehicle demand, focusing mainly on interurban roads. Section 3 establishes the methodology of this research, by describing both data series and the panel data models used to estimate demand elasticities. Section 4 presents and discusses the results. Finally, Section 5 sets out the main conclusions and suggests avenues of further research.

2. State of knowledge

Road demand evolution over time has traditionally been a matter of interest in transport economics, and numerous studies have been conducted in the last decades to identify the key parameters influencing travel patterns (Khademi and Timmermans, 2011; Dargay, 2007; Joksimovic et al., 2006). However, existing research on the evolution of traffic has focused on light vehicle demand, while road freight traffic has received less attention. Basically, the responsiveness of road demand with respect to different factors is measured through the concept of elasticity, by definition the relative change in travel demand induced by a relative change in a certain explanatory variable.

An overview of previous research studies aimed at analyzing and modeling road freight demand are briefly summarized in the following subsection. Then results specifically focusing on freight traffic analysis in toll roads are commented.

2.1. Previous research for free roads

The existing literature concerning road freight demand has mainly focused on modeling commodity or vehicle movements in terms of certain explanatory variables. Demand modeling has been used for different purposes, such as testing transport policy measures, forecasting transport demand, or predicting the impacts of the provision of new infrastructure (Ben-Akiva and de Jong, 2008). According to Nuzzolo et al. (2013), two main technical approaches have been adopted to that end: behavioral models and macro-economic models (both joint and partial share specifications). An overview of their basic characteristics is included in Table 1. Furthermore, a detailed literature in this field can be found in de Jong et al. (2013) and Chow et al. (2010).

Behavioral models simulate mode and route choice, and generally employ disaggregate information, so more detailed policy-relevant variables can be covered (Nuzzolo et al., 2013). By contrast, macro-economic models, which use aggregate information, are aimed at estimating the level and spatial distribution of goods or traffic flows. Within macro-economic models, partial share specifications progressively calculate consecutive steps of transport modeling (generation, distribution, etc.), while direct models simultaneously consider the whole process.

Some interesting findings have been concluded from disaggregate and partial share models. According to Abdelwahab (1998) and Oum et al. (1990), truck price elasticities significantly vary across commodity groups, so elasticities tend to be larger for lower-value commodities compared to higher-value goods. Nuzzolo et al. (2009) identified statistically significant variables for both import and export freight flows. Rich et al. (2011) assessed the extent to which mode substitution in freight transport was affected by lack of alternative freight networks from origin to destination. Additionally, Bröcker et al. (2011) and Meersmann and Van de Voorde (2013) approached the importance of globalization on road freight flows.

Table 1

Overview of the main approaches to model road freight transport. *Source:* Authors' elaboration based on Nuzzolo et al. (2009).

Type of model	Subtype	Level of detail of the data	Aims of the analysis	Examples	Methods employed
Disaggregate models		Individual shipments	Estimate route and/or mode choice	Abdelwahab (1998)	Mixed discrete/continuous choice
		Individual cargo companies		Beuthe et al. (2001) Rich et al. (2011) Yang et al. (2011)	Travel costs minimization Weighted nested logit Intermodal network optimization
Aggregate models	Partial share models	Macro national/regional parameters	Estimate the traffic volume	Nuzzolo et al. (2009) Bröcker et al. (2011) Kveiborg and Fosgerau, (2007)	Category regression, multinomial logit, etc. Gravity modeling Decomposition analysis
	Joint/direct models	Production of economic sectors	Estimate the amount and spatial distribution of goods	Agnolucci and Bonilla (2009) Li and Hensher (2009) Matos and Silva (2011)	ARDL, ECM ARIMA, VAR, BVAR, etc. OLS

Furthermore, other previous research developed aggregate models through direct macro estimates. These studies were aimed at calculating the relationship between heavy goods vehicle demand and certain macro explanatory variables. Gately (1990) employed an econometric analysis of US data to examine the explanatory variables for road freight traffic. He found statistically significant elasticities for both fuel prices (-0.37) and GDP (1.23). More recently, Li and Hensher (2009) identified the key drivers associated with growth of road freight traffic in Australia, and established several time series models to forecast future demand. Matos and Silva (2011) investigated energy efficiency in the road freight transportation sector in Portugal. They adopted an Ordinary Least Square (OLS) estimator and calculated a statistically significant elasticity (0.96) of heavy vehicle demand with respect to national GDP. Nevertheless, both the explanatory variables chosen and the results derived should be approached with caution since many countries – particularly, European ones – have in recent years experienced a decoupling of the growth in road freight traffic from economic growth (Kveiborg and Fosgerau, 2007). Such recent experiences as that in the UK (Agnolucci and Bonilla, 2009; Mc Kinnon, 2007) thus suggest that the relationship between GDP and heavy goods vehicle demand may not be as enduring as often supposed.

Finally, other studies not focused on demand modeling have analyzed additional aspects of road freight transport. Cherry and Adelakun (2012) and Kawamura (2000) calculated perceived value of time and comparative willingness-to-pay for truck operators. Allen et al. (2012) addressed the relationship between heavy vehicle demand, facility location and urban form, while Forkenbrock (1999) estimated external costs for intercity freight trucking. Furthermore, Winebrake et al. (2012) calculated the *rebound effect*, that is, the additional mileage driven as a result of increased fuel efficiency, specifically for heavy vehicle demand.

2.2. Previous research for toll roads

Literature regarding road freight demand for toll roads is still limited and mainly concentrates on aggregate models to estimate the level of traffic. The focus on direct macro-economic models for analyzing these types of roads may be due to two main aspects. First, toll roads are relatively scarce at the international level, what reduces the opportunity of collecting detailed information. Second, the operator of the toll road is especially interested in the traffic volume as a way to anticipate future financial requirements, equipment acquisition, etc., as pointed out by Nuzzolo et al. (2013).

Different research studies can be identified for urban and metropolitan areas. Hirschman et al. (1995) calculated toll elasticities estimates for several tolled bridges and tunnels in New York City. Holguín-Veras et al. (2006) assessed the impact of the Port Authority of New York and New Jersey's time-of-day pricing initiative on the behavior of commercial carriers. Moreover, Arentze et al. (2012) examined how sensitive are truck drivers for possible pricing policies by focusing on short-distance road freight transport, and identified the weight of the vehicle as a key variable. Liang et al. (2009) explored the effects of a toll-by-load policy on the vehicle type constitution pattern. Furthermore, Gupta and Vadali (2008) pointed out the influence that an existing tolling culture on the responsiveness of road freight with respect to tolls.

By contrast, only a very few papers can be found regarding heavy vehicle demand in interurban toll roads and focused on experiences in just a few nations, mainly the United States. They estimated road freight traffic volume through a direct modeling process by using macro variables. We summarize the main results of toll roads from the literature, sorted by country. In the case of the United States, the most consistent research was conducted by Burris and Huang (2013), who analyzed a sample of 12 interurban and metropolitan toll roads throughout the nation during an 11-year period (2000–2010). They established an approach based on time series ADL models, including population, unemployment rate, gas prices, and toll rates as explanatory variables. They found statistically significant results for heavy vehicle demand elasticities with respect to tolls, averaging -0.35 . Concerning fuel price elasticities, values ranged from -0.22 to $+0.14$ (with a mean of -0.03), although user's responsiveness increased (-0.23) when only considering the period during the economic crisis. As for the socioeconomic variables in the model, elasticities with respect to unemployment rate were negative (with a mean of -0.03), likely as a result of the economic downturn. On the other hand, Taft (2004) estimated a toll elasticity of -0.59 for truck volume on

the Ohio Turnpike. Furthermore, Swan and Belzer (2010) estimated diversion of trucks in the Ohio turnpike caused by changes in toll rates applied. Based on an OLS technique, they also forecasted the impact of toll rates on heavy vehicle revenue. Holguín-Veras et al. (2003) analyzed toll lanes for exclusive use by heavy trucks, focusing particularly on Southern California. Finally, Zhou et al. (2009) conducted a survey to quantify the impact of incentives on toll road use by truck drivers in Austin, Texas.

Regarding Norway, Odeck and Brathen (2008) calculated the elasticity of travel demand in 19 Norwegian toll road projects, including cordon toll rings, tolled trunk roads between cities, and tolled roads in peripheral regions. Detailed results provided by type of vehicle show an average toll elasticity of -0.51 for heavy goods vehicles. As for Australia, Hensher et al. (2013) investigated the response of road freight operators to price signals under different access charging schemes, defined by combinations of distance, mass and location. For the case of Spain, Álvarez et al. (2007) estimated the value of time and travel elasticities for both a Spanish toll motorway and for its free parallel road, finding statistically significant elasticities for tolls (-0.39) and fuel prices (-0.09).

As can be seen, the existing literature on interurban toll roads leaves some important aspects to be investigated. First, previous studies have focused on light vehicle demand, so that little attention has been paid to road freight traffic in tolled infrastructure. Furthermore, statistic models hardly established a macro approach to identify the key explanatory variables of heavy vehicle traffic, especially concerning the economic growth. In this respect, it is necessary to assess to what extent GDP constitutes a suitable explanatory variable for heavy goods vehicle demand in toll roads, and to explore possible alternatives. It is also important to include new econometric techniques to analyze heavy vehicle demand for the specific case of toll roads. In this respect, we use a panel data specification, combining both time series and cross-sections observations, which provides different advantages such as more variability and efficiency, and is better suited to study the dynamics of change (Gujarati and Porter, 2004). Finally, few studies (Burris and Huang, 2013) have analyzed the impact of an economic crisis on toll road freight demand. For the case of Spain, no previous studies have been undertaken specifically to investigate heavy vehicle traffic evolution over time.

3. Methodology

This section presents the data collected for the analysis of heavy vehicle demand on Spanish toll roads, as well as the methodology we followed to develop the dynamic panel data approach.

3.1. Previous data analysis

In order to estimate the demand equation for heavy vehicle traffic, we establish a dynamic panel data corresponding to 14 Spanish toll roads observed between 1990 and 2011. The sample includes those toll highways whose traffic data series are long enough for the statistical approach adopted in this paper, which is described below. Other existing tolled sections in Spain – those toll highways belonging to the second phase of tender in the Spanish toll network, whose operation started after 1998 – have traffic data series too short to be included in the analysis. Every toll highway included in the sample has a free parallel conventional road competing with it. The analysis thus focuses on toll roads with a free alternative of lower quality.

The dependent variable of the demand equation is the total veh-km travelled (VKT) for heavy vehicles in each toll road. These data have been collected from the statistics of the Spanish Ministry of Transportation (Ministerio de Fomento, 2012). Although traffic data from shorter tolled sections were available – each approximately 20 km in length – we have only considered average data for entire toll roads in order to avoid spatial correlation problems in the models, since data from short sections in the same highway are highly dependent on each other. That is, traffic volumes from consecutive road sections are very similar and clearly not independent. In this respect, we should note that more detailed information regarding road freight demand could not be included, since Origin–Destination data is not available for the Spanish road network. Nevertheless, the macro data available is suitable for the type of analysis initially pursued.

Three kinds of explanatory variables have been included in the demand equation (see Table 2): demand volume of previous years, socioeconomic variables, and generalized cost parameters. The demand variable ($VKT_{(-1)}$) consists of a lag of the traffic volume, a term needed due to the dynamic nature of the panel. Within socioeconomic variables, we have considered several alternatives. Firstly, we take GDP since it is the most common socioeconomic variable used to explain road freight traffic growth. Secondly, we consider combined GDPs only of highly transport-intensive activities (GDP_{TI}). These sectors have been selected among those activities with the highest road freight transport intensity (RFTI) in Spain according to Alises et al. (2014), as well as their data availability. Particularly, we include Industry, Agriculture and Construction, which also comprises mining activities according to the Spanish statistical accounts. As can be seen, GDP_{TI} excludes those sectors with little or no impact on road demand, such as financial services, public administration, and education.

Finally, GDP of the industrial sector alone (GDP_{ind}) is included, as greater influence on toll road traffic can be expected from this variable. Industry generally comprises high value-added commodities, at which heavy vehicle transport generally show lower toll elasticities according to EPA (2011). Therefore, trucks carrying industrial products tend to show less reluctance to pay tolls when compared to heavy vehicles transporting lower-value-added goods. Furthermore, industrial commodities are usually moved over long distances, at least in the case of Spain, where manufacturing centers are

Table 2
Explanatory variables included in the analysis.

Dependent variable	Explanatory variables			
	Previous demand	Socioeconomic	Generalized cost	
			Toll	Fuel
VKT (Heavy Vehicles)	VKT (-1)	<ul style="list-style-type: none"> • GDP (provincial) • GDP (national) • GDP transport-intensive sectors (prov.) • GDP transport-intensive sectors (national) • Industry GDP (prov.) • Industry GDP (national) 	Toll prices (heavy vehicles)	Fuel cost (€/km): Diesel prices & efficiency

concentrated in certain regions. In these conditions, toll roads become a more attractive option when compared to the available free alternative of lower quality. By contrast, construction activities in Spain are mainly of an intra-regional nature (Vassallo et al., 2013) and generate medium- and short-distance trips, so that a smaller impact on toll road traffic can be expected. Data have been collected from the Spanish National Statistics Institute (INE).

Total or national traffic in the country is also an explanatory variable sometimes included in aggregate models (Swan and Belzer, 2010) with the aim to consider the ups and downs of overall demand. At least in the case of Spain, traffic in toll roads has not empirically shown the same trend from free roads in the country, especially concerning high capacity roads. While the core of the current toll road network started its operation during the mid-sixties, free highways were built much later, by gradually expanding high capacity sections (+363.7%) between mid-1980s and mid-2000s. As a result, each kind of roads experienced a far different trend over time. For instance, traffic in free roads grew by 299.0% between 1990 and 2007, mainly due to the extension of the network and improved accessibility in this period, while increases of traffic in toll roads (+128.8%) were significantly smaller (Ministerio de Fomento, 2013). Therefore, the gradual and meaningful expansion of free highways in Spain during the period analyzed does not make national VKT a suitable variable to consider the ups and downs experienced by overall road demand in the country.

As an alternative to capture the effect of free roads, we have considered total VKT in the corridor where the toll road is located because the infrastructure in these corridors has remained stable over the period of analysis. This method requires the inclusion of traffic data regarding the free parallel routes competing with the toll roads selected. A suitable technique to analyze this situation is a Seemingly Unrelated Regression (SUR) model, since it enables to evaluate the potential simultaneous relationship between demand in both roads – toll and free ones –, which may be affected by the same or different explanatory variables. As pointed out by Zellner et al. (2006), SUR models establish a system of equations related to each other, in which the error terms are correlated across equations, that is, the variance-covariance matrix is not diagonal. This joint estimation of demand volume in both toll and free roads leads to unbiased and more precise estimates of the regression coefficients. The SUR approach also allows us to test the magnitude of the relationship between traffic of competing roads through the Breusch–Pagan (BP) test. The results obtained in our sample for the BP test make it clear that, from a statistical point of view there is no difference between a SUR model and the dynamic panel data technique we propose in this paper, so the latter is the approach we finally followed in this research.

Other socioeconomic variables available in the Spanish statistical accounts, such as population or size of the vehicle fleet, have been discarded for two main reasons. Firstly, they are highly correlated with other socioeconomic variables included in the model. Secondly, weaker relations with traffic evolution were observed when compared to other explanatory variables considered in the model, especially after the beginning of the economic crisis of 2008. Due to the macro nature of the analysis, transport-specific variables such as type of commodity carried, and type of trip, have not been included in the model.

As mentioned before, three kind of explanatory variables are included in the demand equation: previous demand, socioeconomic and generalized cost variables. Specifically, the equation incorporates a lag of the traffic volume ($AADT_{(-1)}$), a Socioeconomic variable and two Generalized cost parameters (Toll and Fuel), what results in a total of 4 categories:

$$VKT = f(VKT_{(-1)}, \text{Socioeconom.}, \text{Toll}, \text{Fuel}) \quad (1)$$

According to Table 2, we consider several alternatives within these four categories, particularly in the socioeconomic one. This methodology then allows us to calibrate several versions of the model just by taking one variable from each of the groups of the demand equation. Therefore, by running all the available combinations of variables, we can establish up to 6 different versions of the model specification we propose. This variability improves the analytical capability of the methodology applied. Further details of the demand equation and the methodology specification are provided in Section 3.2. Additionally, a precise definition of each variable included in Table 2 is presented in the Appendix.

Regarding socioeconomic variables, two levels of data have been considered in the analysis: provincial level and national level. With the aim of better measuring the influence of local socioeconomic characteristics on heavy vehicle demand, data

have been collected at the provincial level. In Spain, a province is a geographical and political subdivision of a region. In this respect, each toll road is assigned the socioeconomic data from the provinces it crosses, as detailed in Appendix A. Furthermore, data at the national level have also been tested since the panel analysis is applied to different toll roads spread throughout the country. In this respect, national parameters are expected to constitute a good proxy of socioeconomic data, not for any particular road but for the panel as a whole. Furthermore, national data may be a satisfactory explanatory variable, as some regions in Spain bear a noticeable volume of pass-through road freight traffic, generally less related to local activities. Monetary socioeconomic variables (total GDP and combined GDPs of certain sectors) have been deflated by the Consumer Price Index (CPI) to reflect their real value over time.

With regard to Generalized cost variables, historical toll rates – expressed in euro/km – were collected from the statistics of the Spanish Ministry of Transportation (Ministerio de Fomento, 2012). As for fuel cost, we assume some simplifications when including this parameter in the analysis. A *Fuel cost* variable is established by taking into account not only diesel prices – expressed in euro/liter – but also fuel consumption (liter/km) for heavy vehicles. It allows us to reflect real fuel costs when driving (euro/km) and include the *rebound effect* due to the progression in fuel efficiency experienced by trucks over time. Furthermore, this procedure clearly constitutes a more realistic approach, since taking into account only diesel prices could lead to a misestimate of the fuel influence on travel demand. For calculating fuel consumption over the 1990–2011 period, we introduce linear improvements in fuel efficiency, from average 1990 values pointed out by the Ministry of Transportation (MOPU, 1990), to current levels made available by the Ministry of Industry (Idae, 2011). Both toll rates and fuel costs have been adjusted to inflation by using the CPI.

Additionally, several subsamples have been proposed for this dynamic panel data approach. Apart from working with the whole sample, separate analyses have been conducted for coastal and interior roads in Spain. Traditionally, road freight traffic near the coast has been highly dependent on local activities such as construction, which experienced a great boom during the 1990s and early 2000s due to the development of new residential areas promoted by local governments. Furthermore, some regions near the coast (Catalonia, Valencia, the Basque Country) are among the most industrialized areas in the country. By contrast, toll roads in the inner part of the peninsula generally pass through less developed areas, with less economic activity. Then, it may be expected that heavy vehicle demand in coastal roads responds to provincial socioeconomic variables, whereas demand in interior roads should be considered in the light of national, rather than regional, data. This distinction leads to the attempt to evaluate whether road freight traffic in coastal and interior toll roads show different behavior responses with respect to both national and provincial socioeconomic data.

At this point, we want to emphasize the analytical capability of our methodology. Given the explanatory variables considered as displayed in Table 2, the panel data allows us to construct up to 18 versions of the model, if we take into account the 3 possibilities (all, coast, interior) regarding the size of the sample. Thus, many and rapid cross-comparisons can be conducted in order to identify the most suitable socioeconomic explanatory variables for heavy vehicle demand.

Table 3 provides an overview of the evolution of some of the provincial socioeconomic variables for all the toll roads selected before and after the economic recession. It shows the information for three special years in the sample: the starting point (1990), the peak reached just before the economic crisis (2007), and the last year (2010) where socioeconomic data is available at the provincial level. The data shows the long and strong economic growth experienced in Spain during the 1990–2007 cycle, when national GDP increased by 78.0%. For the provinces crossed by the toll roads selected, the data displayed shows average growth rates of 76.5% for total GDP, 44.9% for GDP_{Tt}, and 34.6% for GDP_{Ind}. This period of prosperity has been followed by a significant deterioration, since 2008, of the nation's economic performance. National GDP fell by 7.4% between 2007 and 2011. Provincial socioeconomic data also shows significant average reductions from 2007 to 2010 for total GDP (−5.2%) as well as for GDP_{Tt} (−15.9%) and GDP_{Ind} (−15.2%).

Table 3
Average heavy vehicle demand for Spanish tolled motorways considered and provincial socioeconomic data (1990–2010).

Tolled roads	VKT			GDP			Intensive transport GDP			Industry GDP		
	1990	2007	2010	1990	2007	2010	1990	2007	2010	1990	2007	2010
Montmeló–La Jonquera	251.4	528.1	406.8	49.7	89.9	84.7	18.3	25.1	21.1	14.3	16.8	14.6
Barcelona–Tarragona	256.8	481.0	336.4	50.3	90.5	85.4	18.6	25.5	21.4	14.5	17.0	14.8
Zaragoza–Mediterráneo	180.9	179.9	111.8	16.8	30.3	28.9	6.5	9.5	8.0	3.9	4.9	4.5
Villalba–Adanero	54.9	121.58	87.2	54.8	105.2	101.5	12.8	20.3	16.5	8.5	9.9	8.1
Sevilla–Cádiz	16.1	69.0	46.4	17.5	30.6	28.6	6.0	7.4	5.9	2.5	3.1	2.6
Tarragona–Valencia	180.2	448.5	265.9	27.1	47.5	44.1	9.9	13.9	11.4	6.3	7.5	6.5
Valencia–Alicante	53.2	131.9	74.4	26.5	48.2	44.2	8.5	12.6	10.2	5.4	6.3	5.4
Bilbao–Zaragoza	107.7	203.1	155.6	23.4	40.9	39.3	8.6	13.1	11.3	6.0	8.3	7.3
Burgos–Armiñón	41.2	173.8	124.1	6.3	10.9	10.2	2.9	4.3	3.7	2.1	3.0	2.5
León–Campomanes	22.3	52.4	45.7	11.5	18.1	17.2	3.4	5.6	4.3	1.8	4.5	2.0
Montgat–Mataró	9.8	21.0	15.7	44.4	79.5	74.9	16.3	22.2	18.7	13.1	15.4	13.3
Bilbao–Behobia	86.1	188.6	171.9	17.5	29.8	28.9	6.1	9.4	8.4	4.6	6.4	6.0
Tudela–Iruzun	25.2	180.1	151.8	5.5	9.6	9.6	2.4	3.5	3.3	1.7	2.3	2.2
San Cugat–Manresa	4.5	26.7	16.8	44.4	79.5	74.9	16.3	22.2	18.7	13.1	15.4	13.3
Units	M veh-km			10 ³ M€ (constant)			10 ³ M€ (constant)			10 ³ M€ (constant)		

Heavy vehicle demand has experienced trends similar to those of socioeconomic variables. For the selected toll roads, road freight traffic rose on average by 188.1% over the period 1990–2007, in line with the economic growth in the country. Trends have changed since the beginning of the crisis, and demand levels in 2010 were 27.7% lower than the peak reached in 2007. These sharp variations observed in the tolled network during the last 20 years make Spain an interesting case to be analyzed as well as useful in testing the robustness of the models.

3.2. Dynamic panel data methodology specification

In this section we present a dynamic panel data methodology for studying the evolution of heavy vehicle demand in toll roads. It allows us to estimate demand elasticities with respect to explanatory variables included in Table 2. The form proposed for the estimation models is:

$$\ln \text{VKT}_{it} = \eta_i + \lambda \ln \text{VKT}_{i,t-1} + \beta_1 \ln \text{Fuel}_t + \beta_2 \ln \text{Toll}_{it} + \beta_3 \ln \text{Socioec}_{it} + \varepsilon_{it}$$

With provincial socioeconomic data : $t = 1990, \dots, 2010; i = 1, \dots, 14$

With national socioeconomic data : $t = 1990, \dots, 2011; i = 1, \dots, 14$

(2)

where \ln refers to natural logarithm. Given the dynamic nature of the analysis, the equation includes a lag of the demand variable ($\text{VKT}_{i,t-1}$). *Fuel* denotes fuel costs assumed by trucks in euro/km. *Toll_{it}* denotes toll rate (euro/km) applied in road i for year t . Finally, *Socioec_{it}* denotes different socioeconomic data (total GDP, GDP_{C+t} and GDP_{ind}) assigned to road i , either at the provincial or national level. Regarding the rest of the parameters, β_k is the short-run elasticity of road demand with respect to explanatory variable k ; λ measures possible autocorrelation in traffic data series; η_i denotes unobserved individual effects, that is, constant and specific factors for each tolled road, not accounted for by any of the other variables in the models; finally, ε_{it} is the residual or idiosyncratic error.

Regarding initial conditions, we assume (Blundell and Bond, 1998) that η_i and ε_{it} are independently distributed across i and have the familiar error components. As pointed out by Graham et al. (2009), the main issue to be addressed in the context of dynamic panel estimation is correlation between the lagged dependent term ($\text{VKT}_{i,t-1}$) and the unobserved cross-section individual effects (η_i). This fact greatly limits estimators to be applied. The Ordinary Least Squares (OLS) estimator for λ is then inconsistent (Bond, 2002; Hsiao, 1986) and biased upwards, at least in large samples (Nickell, 1981; Blundell et al., 2000). The Within Groups (WG) estimator eliminates this source of inconsistency by transforming the equation to eliminate η_i , but gives an estimate of λ that is biased downwards, especially in short panels (Bond, 2002; Blundell and Bond, 1998). Therefore, a consistent estimate of λ can be expected to lie between the OLS and WG estimates (Arellano and Bond, 1991; Bond et al., 2001).

Better estimates can be calculated with a Generalized Method of Moments (GMM) approach, proposed by Larsen (1982). Within this technique, Eq. (2) is differenced to eliminate the individual effects:

$$\Delta(\ln \text{VKT}_{it}) = \lambda \Delta(\ln \text{VKT}_{i,t-1}) + \beta_1 \Delta(\ln \text{Fuel}_t) + \beta_2 \Delta(\ln \text{Toll}_{it}) + \beta_3 \Delta(\ln \text{Socioec}_{it}) + \Delta \varepsilon_{it}$$
(3)

In this expression, we find that $\Delta(\text{VKT}_{i,t-1})$ is correlated with $\Delta \varepsilon_{it}$, since $\text{VKT}_{i,t-1}$ and $\varepsilon_{i,t-1}$ are clearly correlated. To solve this problem, Arellano and Bond (1991) adopted the so-called difference GMM estimator (GMM-DIFF), which includes an instrumental variables (IV) approach. The GMM-DIFF estimator assumes that values of the dependent variable lagged two periods or more ($\text{VKT}_{i,t-s}$, for $s \geq 2$) are valid instruments for the lagged dependent variable in the differenced equation, $\Delta(\text{VKT}_{it})$. Then, we can establish a set of *moment conditions* that would be satisfied by the true values of the parameters to be calculated (Elhorst, 2012):

$$E(\ln \text{VKT}_{i,t-s} \Delta \varepsilon_{it}) = 0 \text{ for } t = 3, \dots, T \text{ and } s \geq 2$$
(4)

In this respect, if we assume an absence of serial correlation, in the differenced Eq. (3) it can then be easily seen that an additional valid instrument is available with each additional time period. Nevertheless, due to some problems that can arise when too many instruments are considered (Roodman, 2009), we have opted for using only the first lag available in each time period. Furthermore, according to Judson and Owen (1999), limiting the number of instruments does not materially reduce the performance of this technique.

The GMM-DIFF approach generates consistent and efficient estimates of the parameters (Rey et al., 2011), among other attractive properties noted in the literature (Graham et al., 2009). However, it suffers from very low precision as the value of λ increases towards unity (Blundell and Bond, 1998), particularly at values around 0.8 and above. In these cases, lagged levels $\text{VKT}_{i,t-s}$ become weak instruments in the differenced Eq. (3), which can result in serious bias problems.

To overcome the *weak instrument* problem for persistent series, Arellano and Bover (1995) and Blundell and Bond (1998) suggested a system GMM estimator (GMM-SYS), where the instruments used in the levels equations are lagged first differences of the series. It allows yielding $(T - 2)$ additional moments:

$$E[\varepsilon_{it} \Delta(\ln \text{AADT}_{i,t-1})] = 0 \text{ for } t = 3, \dots, T$$
(5)

Exploiting these additional moment conditions can produce some advantages in terms of precision, efficiency, etc., in cases where the autoregressive parameter is only weakly instrumented (Arellano and Bover, 1995). However, despite being smaller, the finite sample bias of the GMM-SYS estimator is generally upwards, in the direction of OLS levels (Blundell and Bond,

1998). Finally, it must be noted that the most suitable technique in each case can change depending on the size of the panel (Judson and Owen, 1999).

The most widely used tests to check the validity of hypotheses assumed in GMM estimators are the m1 and m2 tests, as well as the Sargan test (González and Marrero, 2011). The m1 and m2 tests, proposed by Arellano and Bond (1991), check that no first and second-order serial correlations are observed in the estimated residuals ε_{it} , by meeting some requirements (see more details in Section 4.4). Not fulfilling the needed requirements in m1 and m2 tests can reveal inconsistency of estimates (Garín-Muñoz, 2006) or the possibility of improving the instruments chosen (Rey et al., 2011).

Additionally, the Sargan test checks the validity of the instruments used in the model by detecting possible correlation between the instruments and differenced residuals $\Delta\varepsilon_{it}$. As noted by Böckerman et al. (2009), the Sargan test can have extremely low power when using too many instruments in the GMM model, so that results from the test should be interpreted with care (Graham et al., 2009). In order to limit this problem, we have adopted the alternative procedure proposed by Roodman (2009) that consists of using only the first lag instead of all available lags for instruments in the demand equation.

Further details about validity tests used in this paper are displayed in Section 4.4 which analyzes robustness of results.

4. Modeling results and discussion

This section summarizes the main findings from the analysis of heavy vehicle demand evolution over time applied to Spanish toll roads. First, general aspects of the panel data approach adopted in this paper are shown. Next, we present the main results of road freight demand elasticities and discuss the suitability of explanatory variables included in the models. Finally, the robustness of results is discussed.

4.1. General aspects

This paper develops an original approach to identify the key socioeconomic explanatory variables influencing road freight traffic. This research is based on estimates of demand elasticities with different panel data specifications. We have included some new aspects in our analysis:

- Stability of results is checked by gradually calibrating new runnings of the model with a longer time period considered in the analysis. Then, the traditional static approach that presents elasticity results for a specific period has been exchanged for a time-dependent approach which includes the calculation of demand elasticities over time when the period of analysis is extended. In this respect, those variables with significant variations in their demand elasticities over time cannot be considered as suitable to explain the evolution of road demand. Then, this paper presents a different approach from that one proposed by Holguín-Veras et al. (2011), one of the few papers studying temporal stability of parameters. Based on an Origin–Destination survey in Colombia, these authors developed a panel formulation to analyze road freight demand, and included time-dependent parameters in the model specification to check for temporal stability.
- As mentioned in Section 3, the methodology includes a noticeable variety of explanatory variables with regard to socioeconomic data, period of time considered, size of the sample, etc. This variety enables a direct and deeper comparison of available alternatives, and makes it easier to identify which variables explain road demand evolution in a better way.
- Very little research (Burris and Huang, 2013) on toll road demand has included the period of economic crisis – from 2008 on – in the analysis. Studying such an interesting case as the Spanish tolled network, with a significant reduction of heavy vehicle demand since 2008, allows us to test the robustness of the results when the economic outlook changes dramatically.

The great diversity of models presented in the methodology does not make it possible to show the results for each and every one of the alternatives available. In this paper, we focus on the behavior of some variables, especially socioeconomic ones due to their great explanatory potential for road demand. Furthermore, different figures summarize the evolution of demand elasticities as described above, in order to make the analysis more appealing and easier to grasp. The following subsection presents and discusses the most interesting results from all the models considered in the analysis.

4.2. Analysis of explanatory variables influencing heavy vehicle demand

This subsection summarizes the estimates of heavy vehicle demand elasticities by using the panel data methods described before (OLS, WG and GMM), when taking into account all the variables considered according to Table 2. Results are sorted by socioeconomic variables (total GDP; GDP of highly transport-intensive sectors, GDP_{TI} ; and Industry GDP, GDP_{Ind}), as they may be the key explanatory variables of demand evolution.

Table 4 includes detailed results for a certain demand model applied to e.g. the 1990–2007 period, characterized by long and deep economic growth in Spain. The model considers provincial GDP, toll rates and fuel cost (€/km) as explanatory variables for heavy vehicle traffic. According to Arellano and Bond (1991) and Bond et al. (2001), the λ estimates for OLS-pool (0.992) and WG (0.212) are biased upwards and downwards, respectively. This fact automatically invalidates the demand results obtained for the rest of the explanatory variables, since they are also biased. Regarding the GMM-DIFF estimator,

Table 4

Estimation of travel demand elasticities for the 1990–2007 period, through different panel data estimators.

	OLS-pool		WG fixed effects		GMM-DIFF		GMM-SYS	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
VKT (–1)	0.992	0.0000	0.212	0.0000	0.393	0.0004	0.952	0.0000
GDP (prov.)	–0.013	0.1307	2.021	0.0000	1.003	0.0000	0.007	0.2365
Fuel cost	0.136	0.5455	–0.098	0.3775	–0.387	0.0017	–0.034	0.4465
Toll	–0.017	0.1288	–0.224	0.0000	–0.333	0.0064	–0.069	0.0011
R ²	0.9922		0.2845					
m1-test					–1.524	0.0477	–1.966	0.0492
m2-test					–0.070	0.7438	–1.794	0.0726
Sargan test					14.0	0.5255	14.0	0.9990

the elasticity result for $VKT_{(-1)}$ (0.393) comfortably falls between that of OLS and WG, and is significantly different from zero, so demand elasticities calculated through this technique are not biased. However, the λ estimate for the GMM-SYS estimator (0.952) is very close to that from the OLS-pool, which again suggests some kind of bias in the results. This has been a circumstance frequently met with in conducting the analysis, so in the end we have chosen the GMM-DIFF approach for the forward analysis. Several reasons support this choice. In this particular case, problems regarding persistence of series are not found with GMM-DIFF estimators, as λ estimates for all the models developed below range from 0.263 to 0.647, that is, clearly lower than 0.8. Furthermore, the period of time is fairly long, with at least $T = 20$. Finally, choosing a GMM-DIFF approach rather than a GMM-SYS method limits some problems arising when robustness tests are applied (see Section 4.4). Then, the GMM-DIFF is ultimately the panel estimator chosen to develop the analysis of heavy vehicle demand evolution.

For the particular case shown in Table 4, as well as for the results presented below, detailed comments addressing the robustness of the estimates are displayed in Section 4.4.

Previous studies often conclude their research at this point. We now introduce some variability in the analysis by calibrating new models with time periods progressively extended over time. An illustrative example can be seen in Fig. 1. It shows elasticity results from models including toll rates, fuel cost and total GDP either at a provincial level (sub Fig. 1a) or at a national level (sub Fig. 1b) as explanatory variables. Furthermore, each subfigure reveals how demand elasticities vary when the time period considered changes over time. The y-axis measures demand elasticities obtained through the panel estimator that we ultimately selected (GMM-DIFF). The x-axis indicates the last year considered in the time period, taking 1990 as the starting point, so it allows for the analysis of the evolution of travel elasticities when an additional year is included in the model. Therefore, subfigures show how elasticities change when the time period gradually varies from 1990–2000 to 1990–2010. It can be easily seen that results shown in Table 4 are displayed in sub Fig. 1a (provincial data) in the right-hand side, specifically for $x = 2007$. As can be noted, all the elasticities have the expected sign: negative for both Toll and Fuel costs and positive for GDP, except in the period since 2010. This circumstance is discussed below.

We want to draw the attention to the analytical capability of Fig. 1. As can be seen, it enables quick and simultaneous comparisons of results for 23 different runnings of the model (11 and 12 models for provincial and national socioeconomic data, respectively), which makes it easier both to observe trends and to identify key explanatory variables. It is then a different approach to study temporal stability of parameters when compared to Holguín-Veras et al. (2011), in which an additional time-dependent coefficient was estimated.

In analyzing the results from Fig. 1, some questions arise. Firstly, results are very similar when considering socioeconomic data either at the provincial or at the national level. Secondly, if we observe the evolution of demand elasticities with respect to GDP, different periods are identified:

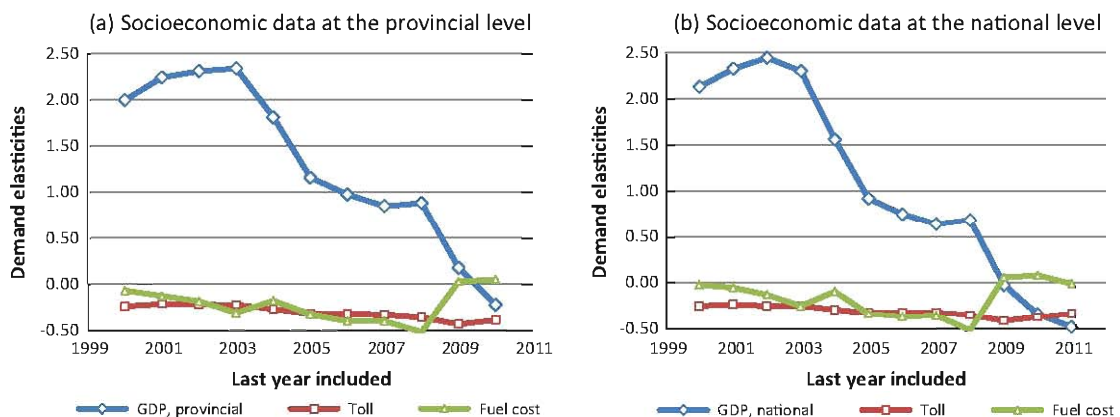


Fig. 1. Demand elasticities when considering provincial GDP (left) and national GDP (right) as the socioeconomic variable in the model.

- Until 2003, demand elasticity moves around 2.0–2.5, which is above the usual values found in the literature. We should note that these results correspond to the peak in the economic growth experienced by Spain during the 1990s and early 2000s.
- Next, GDP elasticities significantly decrease when including the 2004–2008 period. Results range from 0.63 to 1.16, which is in line with previous studies for road freight traffic (Matos and Silva, 2011; Gately, 1990). The decline observed may be caused by two main effects. On the one hand, these years coincide with the last part of the long period of economic growth in Spain. Then, the decrease of GDP elasticities makes clear that, once a certain level of economic development is reached, further growth causes smaller increases in road traffic. On the other hand, a reduction in demand elasticities may reflect some kind of *decoupling effect* resulting from aspects such as: the use of larger vehicles, an increase of average load (Kveiborg and Fosgerau, 2007), a declining share of transport-intensive activities in GDP such as Construction (Liimatainen and Pöllänen, 2013), etc.
- Finally, GDP elasticities fall sharply after the beginning of the economic crisis, with values near zero or even negative. These inconsistent results seem to show that the models are not able to provide a satisfactory explanation for the road freight traffic reduction in Spain, when total GDP is the socioeconomic variable chosen.

Fig. 1 shows that demand elasticity with respect to total GDP experiences great variability over time. As pointed out by Matas et al. (2012), it is often unrealistic to assume a constant elasticity for certain explanatory variables. However, the huge variability of results for total GDP greatly weakens its capability to explain heavy vehicle demand, as both variables show no stability over time. GDP elasticities move from -0.22 to 2.34 when considering provincial data, and range from -0.47 to 2.44 when choosing GDP data at the national level. This makes clear that total GDP does not represent a suitable explanatory variable to be considered as useful in predicting road freight traffic evolution in toll roads.

Results for toll and fuel elasticities are briefly summarized, since including total GDP as an explanatory variable in the models does not lead to good estimates. Toll elasticities present a fairly continuous trend over time, noticeably increasing when we include the crisis. Values range from -0.21 to -0.43 , with a mean of -0.30 . Elasticities with respect to fuel costs, moving between -0.03 and -0.51 , show higher variability. Detailed results for toll and fuel elasticities are commented upon below, when we present more consistent models.

Fig. 2 includes estimates when considering the GDP of highly transport-intensive sectors (GDP_{TI}), either at the provincial (sub Fig. 2a) or the national level (sub Fig. 2b), for the socioeconomic variable in the model. Unlike total GDP, results for GDP_{TI} show significant stability when gradually varying the time period. Demand elasticities move between 0.74 and 1.28 with provincial data, and range from 0.55 to 0.99 when taking national data.

Stability of demand results, even when incorporating the period of the economic crisis, demonstrates that GDP_{TI} is a more suitable explanatory variable. It contrasts with the results shown for GDP elasticities, where there is greater variability over time. There seems to be some reasons for this. While total GDP consists of the aggregation of different heterogeneous sectors of the economy, GDP_{TI} could be a better proxy for road freight mobility. It only refers to transport-intensive sectors (mainly Construction and Industry) and excludes those activities with little effect on road demand, such as public administration, and financial services.

Fig. 2 also demonstrates that changes in heavy vehicle demand trends on Spanish toll roads during the economic crisis cannot be considered an anomalous fact, despite sharp reductions suffered since 2007. GDP_{TI} elasticities in recent years move in the usual range of values of previous years and, therefore, nothing can be concluded in this respect. It makes clear that, if proper explanatory variables are chosen, elasticity estimates show a fairly continuous trend despite dramatic changes in the economic outlook. Furthermore, we want to point out that sub Fig. 2a and b present quite similar results. We could initially expect better performance for provincial data, as they have a stronger relationship with local, specific factors for each road. Nevertheless, GDP_{TI} data at the national level have also been shown to be a good proxy for the whole tolled

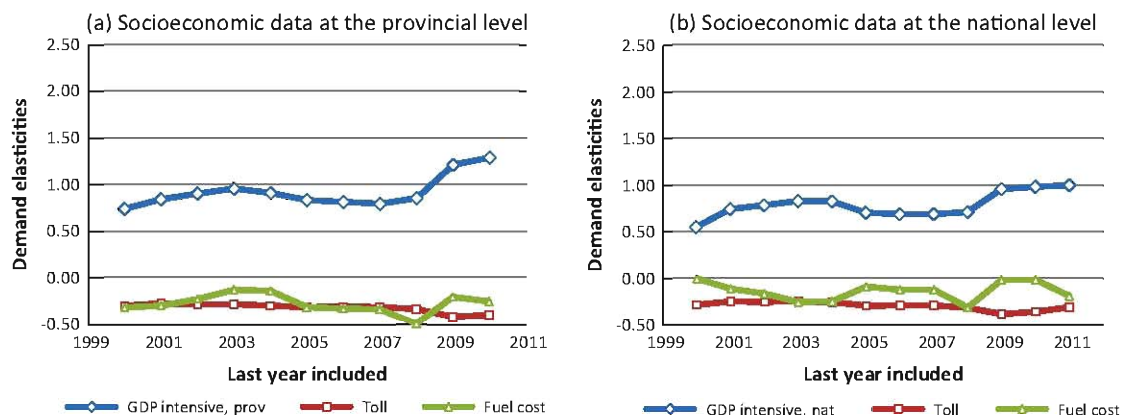


Fig. 2. Demand elasticities when considering provincial GDP of transport-intensive sectors (left) and national GDP of transport-intensive sectors (right) as the socioeconomic variable in the model.

network. This good performance of national GDP_{TI} as an explanatory variable for road freight transport can be attributed to the high proportion of long trips in the tolled high capacity network in Spain, as goods – mainly industrial commodities and agricultural products – need to be transported from the industrialized and agrarian regions near the coast and distributed throughout the inner part of the peninsula.

Next, results concerning demand elasticities with respect to toll rates and fuel costs are discussed. Toll elasticities show a quite stable trend, with values moving from -0.24 to -0.41 and a mean of -0.31 , which is consistent with previous research (Burris and Huang, 2013; Álvarez et al., 2007). This behavior is likely caused by the fact that real toll rates in the sample remain quite stable, as toll rates in Spain are usually adjusted through inflation. It is also noted that toll elasticities increased slightly over time, especially since the beginning of the economic crisis. Regarding fuel elasticities, greater variations are observed. Estimates move from -0.01 to -0.49 , averaging -0.21 , very close to the value provided by de Jong et al. (2010). A wide variety of results are also observed in the literature, as fuel elasticity estimates range from -0.41 (Gately, 1990) to values near zero (Álvarez et al., 2007) or even positive (Burris and Huang, 2013). Our values are in line with previous results, as they usually fall between the highest and lowest estimates found in the literature review. Although the relative position of toll and fuel curves can change over time, both elasticities show values of the same order of magnitude.

Fig. 3 includes elasticity results when Industry GDP (GDP_{Ind}) is the socioeconomic variable adopted in the model. It constitutes the most solid alternative, as all demand elasticities – socioeconomic, tolls and fuel costs – present very constant results over alternative. GDP_{Ind} turns out to be a very stable socioeconomic variable. Elasticities run from 0.91 to 1.16 with provincial data, and from 0.50 to 0.87 with national data. Despite some volatility experienced for particular years, the behavior of GDP_{Ind} can be considered very satisfactory.

Elasticities with respect to toll rates and fuel costs also show significant stability. Trends for toll elasticities are very constant and values move around -0.25 , while those for fuel elasticities are generally lower and lie between 0.0 and -0.28 . These results reinforce the notion that the perception of tolls by potential users is slightly higher than that of fuel costs.

As previously mentioned, heavy vehicle demand evolution in coastal and interior toll roads has also been individually analyzed. Results are quite similar to those previously calculated for the whole sample. The most relevant point has to do with different behaviors often observed in each kind of road (see Fig. 4). As expected, models for coastal roads better fit with socioeconomic provincial data, while interior roads better perform with national data. For instance, GDP_{Ind} elasticities for interior roads move between 0.91 and 1.07 when considering data at the national level, but a larger range of values (from 0.71 to 1.73) is observed with provincial data. As for coastal roads, despite showing solid results in both cases, elasticity estimates with provincial data (0.96 – 1.41) are more consistent than those with national data (0.16 – 0.65). These results can be explained by the strong relationship between road freight demand in coastal roads and local activities such as construction and industry, as well as the high proportion of long trips – less related to local effects – on interior roads.

4.3. Summary of results

Finally, Table 5 summarizes the main elasticity estimates calculated through this panel data approach. As the analysis over time has evidenced, a range of figures seems a more complete and fairer way to present results for demand elasticities, rather than the traditional approach of simply showing a single value for each variable. It gives essential information for traffic forecasts, since it can be generally assumed that the shorter the range of elasticities, the greater its usefulness as an explanatory variable.

Regarding socioeconomic variables, we found that GDP does not show a stable behavior over time, as elasticity values greatly vary in parallel with economic cycles. However, variables such as GDP_{TI} and GDP_{Ind} have a shorter range of values, at both the provincial and the national level, which makes them more reliable explanatory variables to explain heavy vehicle

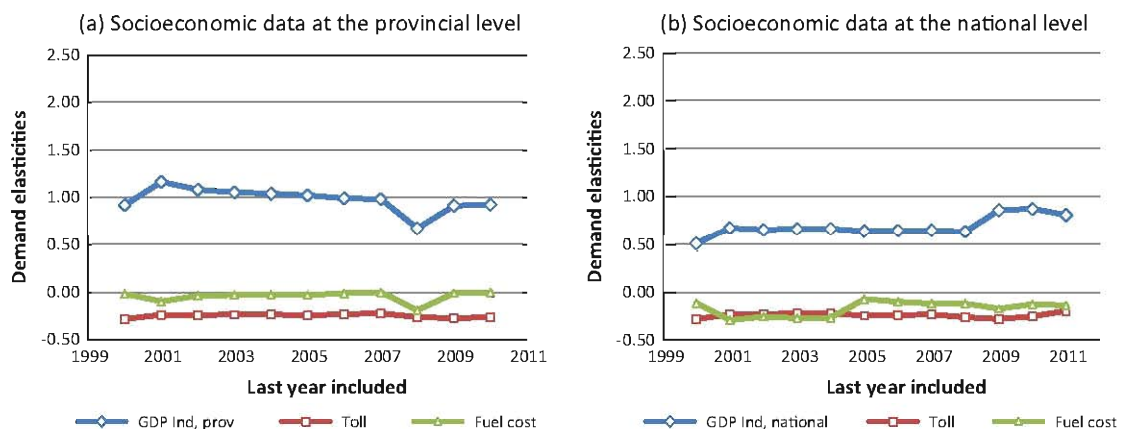


Fig. 3. Demand elasticities when considering provincial Industry GDP (left) and national Industry GDP (right) as the socioeconomic variable in the model.

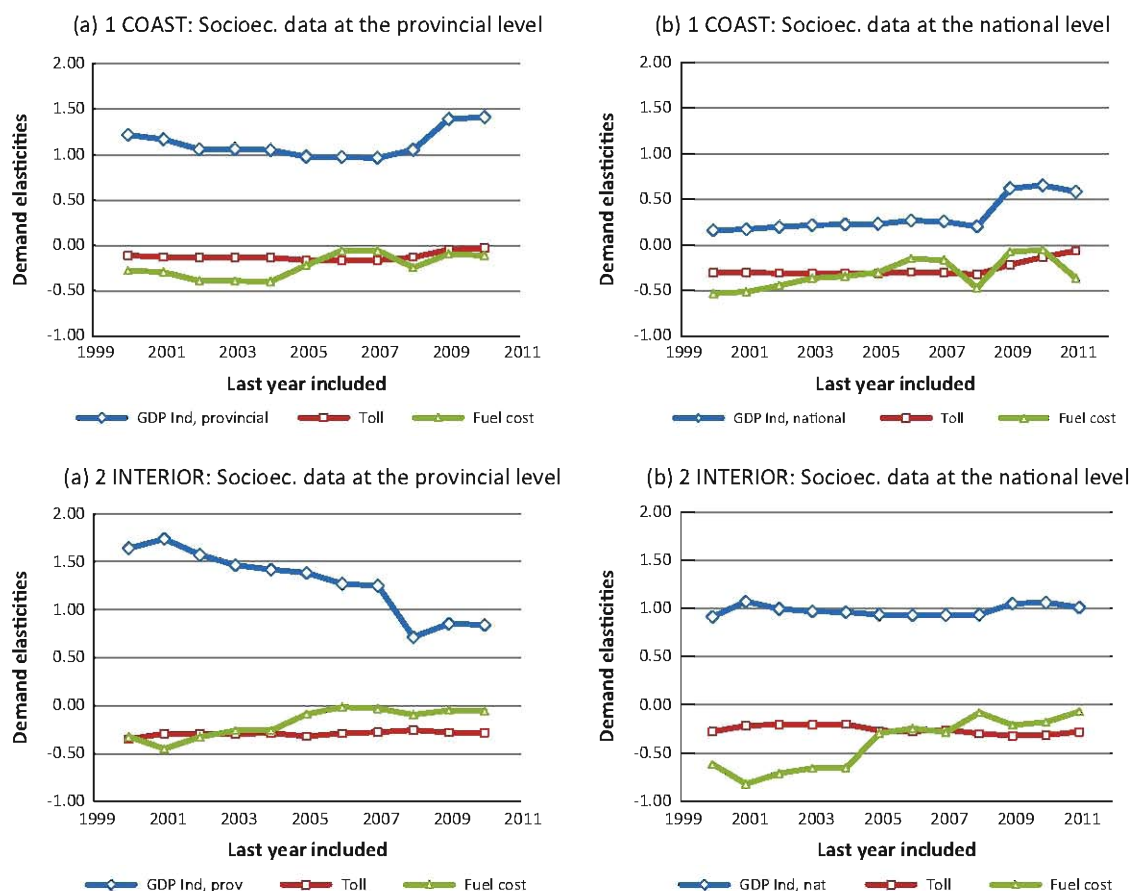


Fig. 4. Demand elasticities when considering provincial Industry GDP (left) and national Industry GDP (right) as the socioeconomic variable in the model, for both coastal (above) and interior roads (below).

Table 5
Summary of elasticity estimations concluded from the analysis for the whole panel.

Variables	Range of elasticities
Provincial socioeconomic variables	
GDP	−0.22 to 2.34
GDP of highly transport-intensive sectors	0.74 to 1.28
Industry GDP	0.91 to 1.16
National socioeconomic variables	
GDP	−0.48 to 2.44
GDP of highly transport-intensive sectors	0.55 to 0.99
Industry GDP	0.50 to 0.87
Toll	−0.43 to −0.19
Fuel costs (€/km)	−0.56 to −0.01

demand. Significant variability of range for fuel costs and tolls responds to the numerous models calibrated because these variables generally show a fairly constant trend in each single model.

4.4. Robustness of results

With regard to robustness of estimations, we have opted for showing one case in detail, displayed in Table 4, and briefly summarize results for the rest of the models calculated. Detailed results for the 69 models included in Figs. 1–3 are very

similar to those from the example commented upon and almost all of them fully meet the requirements pointed out in Section 3.2.

Next, robustness of results regarding m1 and m2 tests is noted. According to González and Marrero (2011), two main conditions must be fulfilled in order to test that no serial correlation is observed in the estimated residuals ε_{it} . First, there should be evidence of negative first-order serial correlation of differenced residuals ($\Delta\varepsilon_{it}$), so that the value of the statistic m1 must be negative, with a p -value preferably below 0.05. Second, there should not be evidence of second-order correlation of differenced residuals, so that the p -value associated to the statistic m2 should be greater than 0.05. Regarding the example detailed in Table 4, results for m1 and m2 tests are consistent with absence of serial correlation in the residuals. As can be noted, the value of the statistic m1 is negative (-1.55) with a p -value of 0.049 (<0.05), while the p -value for the m2 test is 0.495 (greater than 0.05). Robustness of estimates for the rest of the models presented in Figs. 1–3 is very similar to the example from Table 4. The value of statistic m1 moves from -1.893 to -1.109 , with an associated p -value ranging between 0.033 and 0.052 (≤ 0.05). Furthermore, the p -value for the m2 test runs from 0.055 to 0.776 (>0.05). Thus the requirements needed for the Arellano and Bond tests of serial correlation are fully met for all the alternatives shown.

With regard to the Sargan test, the validity of instruments used in the demand equation is checked when the null hypothesis is not rejected. Specifically, González and Marrero (2011) pointed out the convenience of having an associated p -value greater than 0.10. For the case detailed in Table 4, we can observe that the p -value in the Sargan test for GMM-DIFF (0.525) is far above the reference value. Although GMM-SYS also presents a p -value greater than 0.10, values near 1.0 are clear symptoms of low power of the test in that case, since the null hypothesis may exhibit almost zero rejection frequency of the validity of instruments null hypothesis (Baum et al., 2007). These results for the Sargan test support the choice of a GMM-DIFF approach for the analysis rather than a GMM-SYS one. Robustness estimates for the rest of the models are very similar to this case, as the associated p -value for the Sargan test moves from 0.233 to 0.783, again greater than the reference value (0.10) and also not close to 1.0.

5. Conclusions and further research

This paper has developed a panel data methodology to analyze which variables explain heavy vehicle demand evolution over time in toll roads. It establishes a feasible and original alternative, which consists of gradually varying the time period in the model, to analyze the stability of elasticities over time. This approach adds some advantages to the traditional procedure. On the one hand, it enables the identification of those parameters which exhibit a more constant and solid relationship with the dependent variable and, therefore, are more suitable to be chosen as explanatory variables. On the other hand, it makes the analysis more complete, objective, and rigorous. The paper has provided some interesting conclusions.

The first conclusion is that, despite the traditional approach, total GDP does not seem to be the most suitable socioeconomic explanatory variable for heavy goods vehicle demand. The significant variability of GDP elasticities, especially when changes in the economic environment happen, weakens its ability to explain traffic behavior and make long-term traffic forecasts. However, more solid estimates can be made if we take into account only transport-intensive sectors such as construction or industry. Thus excluding from the analysis those activities with low impact on road demand, such as financial services, public administration, and education, clearly improves the performance of total GDP as a socioeconomic variable.

Some comments can be made concerning the socioeconomic variables chosen to forecast heavy vehicle demand evolution. Although better results can be estimated when considering only transport-intensive activities, GDP forecasts for specific sectors of the economy are rarely provided, particularly in the long-term. By contrast, international financial institutions focus their economic projections on total GDP, which makes heavy vehicle traffic forecasts more complicated. In this respect, it would be helpful and desirable that these institutions provide disaggregated GDP projections for the most significant economic sectors. In any case, the results arrived at in this research are useful for understanding the limitations of relying on GDP, in case that is the socioeconomic variable chosen to forecast road freight demand.

The second conclusion points out that traffic decreases experienced in Spanish toll roads in the last years cannot be considered an anomalous fact given the trends shown by socioeconomic data. When proper explanatory variables are chosen for the analysis, elasticity estimates show a fairly continuous behavior despite dramatic changes in both road freight demand and economic growth.

From the results of this paper, some aspects can be highlighted as calling for further research. First, the analysis can be extended to heavy vehicle demand in free high capacity motorways in Spain, in order to check whether each type of road exhibits a different behavior. Furthermore, a trans-national analysis would be of great value to compare the influence that the key explanatory variables studied for heavy vehicles – total GDP, as well as GDP of transport-intensive sectors – can have on toll road demand in different countries. Finally, it would be very useful to include the analysis of the *decoupling effect* in order to improve the performance of total GDP as an explanatory variable.

Acknowledgement

The authors wish to thank the Spanish Ministry of Economy and Competitiveness (MINECO), which has funded the project "EU Support Mechanisms to promote Public Private Partnerships for financing TransEuropean Transport Infrastructure" [TRA 2012-36590].

Appendix A. Description of explanatory variables included in the methodology

AADT (heavy veh./day): annual average daily traffic volume for heavy goods vehicles in each toll road, as recorded in the statistics of the Spanish Ministry of Transportation.

AADT₍₋₁₎ (heavy veh./day): lag of the annual daily traffic volume for heavy goods vehicles in each toll road.

GDP, national (M€): Gross domestic product at the national level, as recorded in the Spanish National Statistics Institute (INE) database. In constant euros.

GDP, provincial (M€): sum of the GDPs from the K provinces crossed by each toll road:

$$GDP_{provincial} = \sum_{i=1}^K GDP_i$$

GDP of highly transport-intensive sectors, national (M€): Gross domestic product of jointly the construction, industry and agriculture sectors at the national level, as recorded in the Spanish National Statistics Institute (INE) database (in constant euros):

$$GDP_{highly\ transport - intensive\ sector, national} = GDP_{constr.} + GDP_{indust.} + GDP_{agric.}$$

GDP of highly transport-intensive sectors, provincial (M€): Gross domestic product of jointly the construction, industry and agriculture sectors from the K provinces crossed by each toll road, as recorded in the Spanish National Statistics Institute (INE) database (in constant euros):

$$GDP_{highly\ transport - intensive\ sectors, provincial} = \sum_{i=1}^K GDP_{constr,i} + \sum_{i=1}^K GDP_{indust,i} + \sum_{i=1}^K GDP_{agric,i}$$

Industry GDP, national (M€): Gross domestic product of the industrial sector at the national level, as recorded in the Spanish National Statistics Institute (INE) database. In constant euros.

Industry GDP, provincial (M€): Gross domestic product of the industrial sector from the K provinces crossed by each toll road, as recorded in the Spanish National Statistics Institute (INE) database (in constant euros):

$$Industry\ GDP, provincial = \sum_{i=1}^K GDP_{indust,i}$$

Toll rate (euro/km): average toll rate applied to heavy goods vehicles in each toll road, as recorded in the Spanish Ministry of Transport statistics. In constant euros.

Fuel cost (euro/km): product of Diesel price and Fuel consumption:

$$Fuel\ cost = Diesel\ price\ (euro/liter) \times Fuel\ consumption\ (liter/km)$$

Diesel prices are collected from the statistics of the Spanish Ministry of Transportation. In constant euros.

Fuel consumption is assumed as a linear progression from average 1990 levels according to the Spanish Ministry of Transportation to 2011 values by the Spanish Ministry of Industry.

Appendix B. Generalized costs for heavy vehicle demand in the Spanish toll network considered (1990–2010)

Variable Units	Toll road	1990	2007	2010
Toll rate €/km (constant)	Montmeló–La Jonquera	0.078	0.070	0.072
	Barcelona–Tarragona	0.088	0.080	0.082
	Zaragoza–Mediterráneo	0.070	0.069	0.071
	Villalba–Adanero	0.164	0.135	0.144
	Sevilla–Cádiz	0.133	0.056	0.058
	Tarragona–Valencia	0.107	0.064	0.066
	Valencia–Alicante	0.108	0.064	0.066
	Bilbao–Zaragoza	0.132	0.082	0.084
	Burgos–Armiñón	0.122	0.064	0.065
	León–Campomanes	0.136	0.079	0.081
	Montgat–Mataró	0.117	0.059	0.061
	Bilbao–Behobia	0.145	0.090	0.091
	Tudela–Iruzun	0.079	0.020	0.021
	San Cugat–Manresa	0.151	0.109	0.111
Fuel price €/liter (constant)		0.400	0.531	0.553
Fuel consumption liter/km		0.400	0.319	0.305
Fuel cost €/km (constant)		0.160	0.169	0.168

References

- Abdelwahab, W.M., 1998. Elasticities of mode choice probabilities and market elasticities of demand: evidence from a simultaneous mode choice/shipment-size freight transport model. *Transp. Res. Part E* 34, 257–266.
- Agnoilucci, P., Bonilla, D., 2009. UK freight demand: elasticities and decoupling. *J. Transp. Econ. Policy* 43, 317–344.
- Alises, A., Vassallo, J.M., Guzmán, A.F., 2014. Road freight transport decoupling: a comparative analysis between the United Kingdom and Spain. *Transp. Policy* 32, 186–193.
- Allen, J., Browne, M., Cherrett, T., 2012. Investigating relationships between road freight transport, facility location, logistics management and urban form. *J. Transp. Geogr.* 24, 45–57.
- Álvarez, O., Cantos, P., García, L., 2007. The value of time and transport policies in a parallel road network. *Transp. Policy* 14, 366–376.
- Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econ. Stud.* 58, 277–297.
- Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. *J. Econ.* 68, 29–52.
- Arentze, T., Feng, T., Timmermans, H., Robroeks, J., 2012. Context-dependent influence of road attributes and pricing policies on route choice behavior of truck drivers: results of a conjoint choice experiment. *Transportation* 39, 1173–1188.
- Baum, C.F., Schaffer, M.E., Stillman, S., 2007. Enhanced routines for instrumental variables/generalized method of moments estimation and testing. *Stata J.* 7 (4), 465–506.
- Ben-Akiva, M., de Jong, G., 2008. The aggregate-disaggregate-aggregate (ADA) freight model system. In: Ben-Akiva, M., Meersman, H., Van de Voorde, E. (Eds.), *Recent Developments in Transport Modelling: Lessons for the Freight Sector*, pp. 117–134.
- Beuthe, M., Jourquin, B., Geerts, J.F., Ha, C.K.N., 2001. Freight transportation demand elasticities: a geographic multimodal transportation network analysis. *Transp. Res. Part E* 37, 253–266.
- Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. *J. Econ.* 87, 115–143.
- Blundell, R., Bond, S., Windmeijer, F., 2000. Estimation in Dynamic Panel Data Models: Improving on the Performance of the Standard GMM Estimators. WP 00/12. The Institute for Fiscal Studies.
- Böckerman, P., Hämäläinen, U., Uusitalo, R., 2009. Labour market effects of the polytechnic education reform: the Finnish experience. *Econ. Educ. Rev.* 28, 672–681.
- Bond, S., 2002. *Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice*. Working Paper CWP09/02. The Institute for Fiscal Studies. Department of Economics, UCL.
- Bond, S., Hoeffler, A., Temple, J., 2001. GMM Estimation of Empirical Growth Models. CEPR Discussion Papers 3048.
- Bröcker, J., Korzhenevich, A., Riekhof, M.C., 2011. Predicting freight flows in a globalizing world. *Res. Transp. Econ.* 31, 37–44.
- Burris, M., Huang, C., 2013. Short-Run Impact of Gas Price Fluctuations on Toll Road Use. Paper Presented (13–3717) at the 92nd Annual Meeting of the Transportation Research Board, January 13–17, 2013, Washington, DC.
- Cherry, C.R., Adelakun, A.A., 2012. Truck driver perceptions and preferences: congestion and conflict, managed lanes, and tolls. *Transp. Policy* 24, 1–9.
- Chow, J.Y.J., Yang, C.H., Regan, A.C., 2010. State-of-the-art of freight forecast modeling: lessons learned and the road ahead. *Transportation* 37, 1011–1030.
- Dargay, J., 2007. The effect of prices and income on car travel in the UK. *Transp. Res. Part A* 41, 949–960.
- Elhorst, J., 2012. Dynamic spatial panels: models, methods and inferences. *J. Geogr. Syst.* 14, 5–28.
- EPA, NHTSA, 2011. *Final Rulemaking to Establish Greenhouse Gas Emissions Standards and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles: Regulatory Impact Analysis*, Washington, DC.
- Forkenbrock, D., 1999. External costs of intercity truck freight transportation. *Transp. Res. Part A* 33, 505–526.
- Garin-Muñoz, T., 2006. Inbound international tourism to Canary Islands: a dynamic panel data model. *Tourism Manage.* 27, 281–291.
- Gately, D., 1990. The U.S. demand for highway travel and motor fuel. *Energy J.* 11, 59–74.
- González, R.M., Marrero, G.A., 2011. Induced road traffic in Spanish regions: a dynamic panel data model. *Transp. Res. Part A* 46, 435–445.
- Graham, D.J., Crotte, A., Anderson, R.A., 2009. A dynamic panel analysis of urban metro demand. *Transp. Res. Part E* 45, 787–794.
- Gujarati, D., Porter, D.C., 2004. *Basic Econometrics*, fourth ed. The McGraw-Hill Companies.
- Gupta, R.S., Vadali, S.R., 2008. Stochastic dominance approach to evaluate optimism bias in truck toll forecasts. *Transp. Res. Rec.* 2066, 98–105.
- Hensher, D.A., Collins, A.T., Rose, J.M., Smith, N.C., 2013. Direct and cross elasticities for freight distribution access charges: empirical evidence by vehicle class, vehicle kilometers and tonne vehicle kilometers. *Transp. Res. Part E* 56, 1–21.
- Hirschman, I., McKnight, C., Pucher, J., Paaswell, R.E., Berechman, J., 1995. Bridge and tunnel elasticities in New York. *Transportation* 22, 97–113.
- Holguín-Veras, J., Sackey, D., Hussain, S., Ochieng, V., 2003. Economic and financial feasibility of truck toll lanes. *Transp. Res. Rec.* 1833, 66–72.
- Holguín-Veras, J., Wang, Q., Xu, N., Ozbay, K., Cetin, M., Poliment, J., 2006. The impacts of time of day pricing on the behavior of freight carriers in a congested urban area: implications to road pricing. *Transp. Res. Part A* 40, 744–766.
- Holguín-Veras, J., Sánchez, I., González-Calderón, C., Sarmiento, I., Thorson, E., 2011. Time-dependent effects on parameters of freight demand models: empirical investigation. *Transp. Res. Rec.* 2224, 42–50.
- Hsiao, C., 1986. *Analysis of Panel Data*. Cambridge University Press, Cambridge.
- Instituto para la Diversificación y Ahorro de la Energía, Idea, 2011. *Conducción eficiente de vehículos industriales*. Ministerio de Industria, Turismo y Comercio.
- Joksimovic, D., Bliemer, M.C.J., Bovy, P.H.L., 2006. Dynamic optimal toll design problem – travel behavior analysis including departure time choice and heterogeneous users. In: *European Transport Conference 2006*, Strasbourg, France, 20th September 2006.
- de Jong, G., Schrieten, A., Van Essen H., Otten, M., Bucci, P., 2010. Price Sensitivity of European Road Freight Transport – Towards a Better Understanding of Existing Results. A Report for Transport & Environment n. 9012–1, Delft, The Netherlands.
- de Jong, G., Vierth, I., Tavasszy, L., Ben-Akiva, M., 2013. Recent developments in national and international freight transport models within Europe. *Transportation* 40, 347–371.
- Judson, R.A., Owen, A.L., 1999. Estimating dynamic panel data models: a guide for macroeconomists. *Econ. Lett.* 65, 9–15.
- Kawamura, K., 2000. Perceived value of time for truck operators. *Transp. Res. Rec.* 1725, 31–36.
- Khademi, E., Timmermans, H.J.P., 2011. Incorporating traveler response to pricing policies in comprehensive activity-based models of transport demand. *Proc. – Social Behav. Sci.* 20, 594–603.
- Kreiborg, O., Fosgerau, M., 2007. Decomposing the decoupling of Danish road freight traffic growth and economic growth. *Transp. Policy* 14, 39–48.
- Larsen, L.P., 1982. Large sample properties of generalized method of moments estimators. *Econometrica* 50, 1029–1054.
- Li, Z., Hensher, D., 2009. Road freight demand in Australia: key drivers and forecasts. *Road Transp. Res.* 18, 15–26.
- Liang, C., Qiaoru, L., Xiaoxiao, L., Xuenjun, Z., 2009. Study of toll-by-load policy effects on vehicle type constitution of parallel network. In: *2009 IEEE International Conference on Automation and Logistics (ICAL)*, 2101–4.
- Liimatainen, H., Pöllänen, M., 2013. The impact of sectoral economic development on the energy efficiency and CO₂ emissions of road freight transport. *Transp. Policy* 27, 150–157.
- Matas, A., Raymond, J.L., Ruiz, A., 2012. Traffic forecasts under uncertainty and capacity constraints. *Transportation* 39, 1–17.
- Matos, F.J., Silva, F.J.F., 2011. The rebound effect on road freight transport: empirical evidence from Portugal. *Energy Policy* 39, 2833–2841.
- Mc Kinnon, A.C., 2007. Decoupling of road freight transport and economic growth trends in the UK: an exploratory analysis. *Transp. Rev.* 27 (1), 37–64.
- McKnight, C.E., Hirschman, I., Pucher, J.R., Berechman, J., Paaswell, R.E., Hernandez, J.A., Gamill, J., 1992. *Optimal Toll Strategies for the Triborough Bridge and Tunnel Authority*. Final Report, Triborough Bridge and Tunnel Authority, New York, December 1992.

- Meersmann, H., Van de Voorde, E., 2013. The relationship between economic activity and freight transport. In: Ben-Akiva, M., Meersman, H., Van de Voorde (Eds.), *Freight Transport Modelling*. Emerald, pp. 17–44.
- Ministerio de Fomento, 2012. Informe 2011 sobre el sector de autopistas de peaje en España. Delegación del Gobierno en las Sociedades Concesionarias de Autopistas Nacionales de peaje.
- Ministerio de Fomento, 2013. Anuario Estadístico. Dirección General de Programación Económica. Subdirección General de Estudios Económicos y Estadísticas.
- Ministerio de Obras Públicas y Urbanismo, MOPU, 1990. Recomendaciones para la evaluación económica, coste-beneficio, de estudios y proyectos de carreteras. Actualización del valor del tiempo y costes de accidentes y combustibles. Servicio de Planeamiento.
- Nickell, S., 1981. Biases in dynamic models with fixed effects. *Econometrica* 49 (6), 1417–1426.
- Nuzzolo, A., Crisalli, U., Comi, A., 2009. A demand model for international freight transport by road. *Eur. Transp. Res. Rev.* 1, 23–33.
- Nuzzolo, A., Crisalli, U., Comi, A., 2013. An aggregate transport demand model for import and export flow simulation. *Transport*. <http://dx.doi.org/10.3846/16484142.2013.820215>, Francis & Taylor.
- Odeck, J., Brathen, S., 2008. Travel demand elasticities and users attitudes: a case study of Norwegian toll projects. *Transp. Res. Part A* 42, 77–94.
- Oum, T.H., Waters II, W.G., Yong, J.S., 1990. A Survey of Recent Estimates of Price Elasticities of Demand for Transport. The World Bank.
- Rey, B., Myro, R., Galera, A., 2011. Effect of low-cost airlines on tourism in Spain. A dynamic panel data model. *J. Air Transp. Manage.* 17, 163–167.
- Rich, J., Kveiborg, O., Hansen, C.O., 2011. On structural inelasticity of modal substitution in freight transport. *J. Transp. Geogr.* 19, 134–146.
- Roodman, D., 2009. A note on the theme of too many instruments. *Oxford Bull. Econ. Stat.* 71 (1), 135–158.
- Swan, P., Belzer, M., 2010. Empirical evidence of toll road traffic diversion and implications for highway infrastructure privatization. *Public Works Manage. Policy* 14, 351–373.
- Taft, B., 2004. Northern Ohio Freight Strategy: Recommendations to Improve Traffic Safety and Congestion. <<http://www.dot.state.oh.us/news/2004/NorthernOhioTruckTraffic/NorthernOhioFreightStrategy10-11-04-Main.pdf/>> (accessed 10.28.13).
- Vassallo, J.M., Ortega, A., Gomez, J., Lopez, J., 2013. Calidad de infraestructuras frente a costes del transporte. Cátedra Amelio Ochoa. Fundación Francisco Corell.
- Winebrake, J.J., Green, E.H., Comer, B., Corbett, J.J., Froman, S., 2012. Estimating the direct rebound effect for on-road freight transportation. *Energy Policy* 48, 252–259.
- Yang, X., Low, J.M.W., Tang, L.C., 2011. Analysis of intermodal freight from China to Indian Ocean: a goal programming approach. *J. Transp. Geogr.* 19, 515–527.
- Zellner, A., 2006. *Seemingly Unrelated Regressions*. H. G. B. Alexander Research Foundation, Graduate School of Business, University of Chicago.
- Zhou, L., Burris, M.W., Baker, R., et al, 2009. Impact of incentives on toll road use by trucks. *Transp. Res. Rec.* 2115, 84–93.